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厦门大学

硕 士 学 位 论 文

建立在韩国隐性波动率指标的基础上的波动预测和每日风险价值模型表现

The volatility forecast and daily Value at Risk models performances based on the Korean implied volatility indexes

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摘 要

全球金融危机后，所有国家感到有必要改善全球金融体系，发挥监管机构的作用，提高各种金融风险管理的方法和技术。本文通过比较论述的有效性的几种方法一些分析来预测市场的风险价值（VaR）及不同形式的波动。风险值是金融风险计量工具之一，为变幻多端市场波动提供了有意义的测量。这篇文章在 KOSPI 的基础上对市场变化内容信号过了评估，这些信号数据都隐含在我们的日常市场风险之中。我们使用 VKOSPI 隐含波动率指数，如 VaR 模型的输入，比较测试结果与其他两个不同的波动输入方面的回溯测试方法。

我们的研究结果为 99％和 95％置信水平，从这个结果来看，我们发现，该模型使用到其他模型的时候，在大多数情况下表现良好。然而，5 天的地平线和波动集群的高电平期间的模型的优越性变得不那么有效。正如预期的那样，GJR-GARCH 性能优于其他两种模型。可见在金融危机时期的急剧变化波动可能会导致最 VaR 模型的问题。显然，我们两个模型试图失败在这些类型的结构性改变一些比别人多。总体而言，模型预测的 VaR 是敏感的持有期的时间跨度，提供了比另一种模型更可靠的信息

关键词：风险价值，隐含波动率，GJR-GARCH;回溯测试

Abstract

After global financial crises all countries feel necessity to improve the global financial system, more develop the role of regulatory agencies, and improve the methods and technologies for management of various financial risks. This paper aims at comparing some analysis of the effectiveness of several approaches to forecast market Value at Risk (VaR). VaR is one of the financial risk measurement tools，which gives a meaningful measurement from the adverse market movements. In this paper we evaluated information content volatility forecast based on the KOSPI implied volatility indexes in a daily market risk. We used VKOSPI implied volatility index as an input for VaR models and compared the testing results with other two different volatility inputs by backtesting methods.

From our results as confidence levels of 99% and 95%, we found out that the model for the most part performs well. However, at 5 day horizon and during high levels of volatility clusters the superiority of the model became less effective. As expected, GJR-GARCH performed better than the other two models. The sharp changes in volatilities, which occurred during financial crisis period, are likely to cause problems for most VaR models. During structural breaks our two models could not perform well. Overall, our results showed that VKOSPI could give more reliable information than the alternative model.

Key Words: Value at Risk; Implied volatility; GJR-GARCH; Backtesting

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Chapter 1 Introduction

1.1 Motivation

We can see that over the last five years global financial markets have experienced unpredictable levels of volatility, for example during the financial crisis, Japan's earthquake and tsunami, the Arab Spring and Eurozone debt crises. Consequently prices and financial conditions have been changing very quickly. Such high levels of volatility show the necessity for improvement: in the timeliness and accuracy of risk limits, exposures and the liquidity of risk measurement. Nowadays because of the growing trading activities among the world's financial management, everyone is paying great attention to risk management skills. If we want to focus on developing good techniques for measuring future financial risks, first we have to accurately define the risks and correctly use its measurements. Nowadays these processes are a very important topic for regulators and risk managers. Consequently, these days risk managers and regulators have carried out a lot of different approaches that can help correctly predict financial risks. The difference of VaR from other risk measures is firstly in defining leverage, correlations and distributions, which helps us to get a correct view of our future risks. This paper is devoted to Value at Risk, like general characteristic of market risk, which is primarily required for the top management of banks and is very popular in modern risk management. For example, the Bank of International Settlements uses Value at Risk as the basis for the establishment of standards of equity relative to risk assets.

1.2 Objectives

This paper aims at a comparative analysis of the predictive accuracy and effectiveness of different models on the calculation of VaR. Implied volatility is one of the most important and well-known parameters in financial markets. It is usually determined from quoted prices for certain derivatives. To find the option price we have to estimate the return volatility of given asset returns. When we know the market price of an option, its pricing model and other parameters such as strike price, maturity, and interest rate, we can extract volatility and estimate that it is implied to the options value, so we can obtain implied volatility. But in our paper we use VKOSPI, which has already been calculated and published by Korean stock market specialists in 2003 (see the appendix for the methods of VKOSPI calculations; this methodology was taken from the Korean stock market website). Our experimental study is to test models based on an implied volatility index, such as the input for a VaR model and the analysis of its performance, by comparing the conditions and the results of different models of VaR. Also, the study shows the classification models of VaR; the emphasis is on the implied volatility index as an input for the VaR calculation method and the testing results using Risk-Metrics and GJR-GARCH. To find out the accuracy and effectiveness of these inputs, we used the Korean stock market.

The Korean financial market underwent several changes before the financial liberalization and opening of their financial market in the 1990s. Those changes implemented significant innovations such as financial derivatives. Since 1996, when the KOSPI200 market opened, the Korean financial derivatives market has grown very fast. In 2002 the KOSPI200 futures and options markets were ranked fourth and first, respectively, in the global stock index futures and options market in terms of trading volume. The KOSPI200 is the most actively traded index in the world. The financial crisis in 2008 affected the world's entire financial system. So, testing VaR models based on the time periods before, during and after the financial crisis is important research for financial institutions.

The purpose of this paper is to determine whether the daily VaR model based on the KOSPI can give meaningful volatility information compared with Risk-Metrics and GJR-GARCH. The output of this research is important because correctly calculated implied volatility and VaR can help investors and financial managers make the right and safe decisions. Inaccuracy in predicting VaR can cause big security problems for the entire financial system.

As a conclusion to this section, we want to mention that the paper seeks to provide answers to the following three research questions:

1) What is the theoretical foundation of the implied volatility and VaR?

2) How can the implied volatility index be applied as an input to VaR?

3) Compared to other models such as Risk-Metrics and GJR-GARCH, how well does the implied volatility index perform as an input for VaR with respect to our financial data?

To answer these questions, several properties have been considered: first we defined implied and realized volatility and considered the information content of implied volatility in VaR. Second we decided to find out how correctly implied volatility helps when modeling VaR. We would then check the accuracy of the risk models by backtesting.

As delimitation, we want to show that in our study we focus on market risk. In the empirical part of our study we use market risk with a financial position in stock indexes, and correlation is not considered. By theory and in most cases, daily return can show weak autocorrelation, which involves fitting an AR, MA and ARMA functions before analyzing VaR. In our study we considered demeaned and uncorrelated returns. During the running regressions, factors such as macroeconomic, political, technological innovations will not be considered, because we are limiting our estimations to VaR.

From our results we can conclude that implied volatility performs better than Risk-Metrics for providing meaningful volatility information in VaR models and accurately modeling the number of violations, also the hypothesis test of independence and conditional coverage was not rejected on testing in-sample case. The GJR-CARCH model was the best model in our study.

1.3 The structure of the paper

This paper consists of five chapters.

Chapter 1 Introduction

This chapter introduces to others the general meaning of the topic, the importance of this topic and the aim of this research. It shows backgrounds and gives a brief explanation of the research objectives of this study.

Chapter 2 Literature Review and Theoretical Framework

This chapter focuses on risk management and Value at Risk. It explains the principles of risk management and shows different ways of calculation VaR. By studying previous research on related topics we have learned how to use VKOSPI as a variable for VaR. We give some basic concepts of VaR, methods and formulas.

Chapter 3 Data and Methodology

The chapter is focused on data and the procedures and models to calculate VaR. Additionally given are explanations of all analyses used to test the hypotheses.

Chapter 4 Empirical Results

This chapter discusses the results of the analysis. We estimate the performance of our models based on our financial data.

Chapter 5 Conclusion. This last chapter is the conclusion of all our main findings. We also present some ideas for further research.

Chapter 2 Literature Review and Theoretical Framework

"All of life is the management of risk, not its elimination."

---Walter Wriston, former chairman of Citicorp

Everything in the world changes and those changes can bring bad or good conditions to us. These changes lead to risk, which results in gain or loss, and risk is something which all of us must come to terms with. So we must manage risk, and determine how to avoid it. This chapter describes the types of risk and shows that financial risks have increased sharply over the last year. The growth of the derivatives market, which should be used only with good risk management, has led to the widespread use of VaR.

As mentioned in Jorion (2000), risk can be defined as the volatility of unexpected outcomes, which can be represented as the value of assets, equity, or earnings. He points out that risk comes from many sources, and can be human-created, such as business cycles, inflation, changes in government policies, and wars, or occur as a result of unforeseen natural phenomena, including weather and earthquakes. Risk also arises from the primary source of long-term economic growth, namely, technological innovations, which can render existing technology obsolete and create dislocations in employment. Firms are exposed to various types of risks, which can be classified as business, market, credit, liquidity, operational and legal risks.

2.1 Risk management

In the last decades the theory and practice of risk management have developed very fast. As a theory development, we can see that nowadays risk management is increasingly taught as a separate subject in finance courses. The transformation of the practice of the risk management has been contributed to by two factors. One of them is the development of new theories and their translation to practical applications. An example of this process is the adoption in the 1970s of the Black-Scholes option pricing model as a practical tool. The other factor has been the development of VaR. The VaR approach began as a methodology for measuring market risks, but it was soon realized that it could do much more than merely provide VaR figures to report to shareholders or guide internal decision-making.

2.1.1 Financial Risk Management

Financial risk management is a process to deal with the uncertainties resulting from financial markets (Horcher, 2005). Managing financial risk is the practice of identifying, assessing, developing actions and making organizational decisions about risks. As Jorion (2000) points out, financial risk management refers to the design and implementation of procedures for identifying, measuring, and managing financial risks. So risk managers need to use forward-looking risk controls. They must know how the instruments respond to risk factors, as well as the range of potential movements in risk factors.

In the 1970s and 1980s, key financial institutions tried to find an accurate risk measurement which would satisfy their risk management purposes and would also give the opportunity to provide consulting services as a business. They worked on these models not just to consider their own risk management purposes, but also to support their management consultancy businesses and to sell to other financial institutions and large corporations. One of the best-known systems was the Risk-Metrics system, developed by J.P. Morgan. To further develop this system, Morgan personnel had to find a system to measure risks across different trading positions, across a whole institution, and aggregate these risks into a single risk measure. This risk measure was VaR, or the maximum likely loss over the next trading day. This measure was derived from a system based on standard portfolio theory, using estimates of the standard deviations and other correlations between the returns of different traded instruments.

2.1.2 Coherence

One of the studies which help to determine the accuracy and sensitivity of risk measures is Artzner (1999). According to their study, the best risk measure should follow four axioms. If the measure follows all these four axioms, we call it coherent. From Danielson (2011), the definition of a coherent risk measures is: “By considering two real-valued random variables: X and Y. A function $\varphi(\cdot): X, Y \to R$ is called a coherent risk measure if it satisfies for X, Y and constant c.

1. Monotonicity

$$X, Y \in V, \quad X \leq Y \quad \Rightarrow \quad \varphi(X) \geq \varphi(Y).$$

If portfolio X never exceeds the values of portfolio Y, the risk of Y should never exceed the risk of X. It means that if our portfolio has lower returns in all cases than another, then the risk of the second portfolio will be greater.

2. Subadditivity

$$X, Y, X+Y \in V \quad \Rightarrow \quad \varphi(X+Y) \leq \varphi(X) + \varphi(Y).$$

The risk to the portfolios of X and Y cannot be worse than the sum of the individual risks - a manifestation of the diversification principle. A merger of two portfolios cannot create another extra risk.

3. Positive homogeneity

$$X \in V, c > 0 \quad \Rightarrow \quad \varphi(cX) = c\varphi(X).$$

When the portfolio value increases by c then the risk increases by the same factor.

4. Translation invariance

$$X \in V, \quad c > 0 \quad \Rightarrow \quad \varphi(X+c) = \varphi(X) - c$$

Adding c to the portfolio is like adding cash, as an insurance, so the risk of X+c is less than the risk of X by the amount of cash c".

2.2. Value at Risk

Below is the basic well-described concept of VaR by Linsmeier and Pearson (1996):

"Value at Risk is a single, summary statistical measure of possible portfolio losses. Value at Risk is a measure of losses due to 'normal' market movements. Losses greater than the Value at Risk are suffered only with a specified small probability. Subject to the simplifying assumptions used in its calculation, Value at Risk aggregates all of the risks in a portfolio into a single number suitable for use in the boardroom, reporting to regulators, or as a disclosure in an annual report. Once one crosses the hurdle of using a statistical measure, the concept of VaR is straightforward to understand. It is simply a way to describe the magnitude of the likely losses on the portfolio. The VaR figure has two main characteristics. The first is that it provides a common consistent measure of risk across different positions and risk factors. The second is that it takes account of the correlations between different risk factors. If two risks offset each other, the VaR allows for this offset and tells us that the overall risk is fairly low. If the same two risks do not offset each other, the VaR takes this into account as well and gives us a higher risk estimate".

As the definition of VaR by Jorion (2005) mentions, VaR is a measure of market risk. It is the maximum loss which can occur with X% confidence over a holding period of t days.

Tanna (2006) points out that VaR is the expected loss of a portfolio over a specified time period for a set level of probability. VaR measures the potential loss in market value of a portfolio using estimated volatility and correlations. It is a measurement within a given confidence interval, typically 95% and 99%. The well-known concepts of VaR try to measure the possible losses of the portfolio under 'normal' circumstances. The definition of normality is a key condition for the estimation of VaR and is a statistical concept; its importance varies according to the VaR calculation methodology being used. Nowadays VaR may be used by any organization exposed to financial risk. VaR is useful as a tool of risk management for institutions including commercial banks, which use VaR measures to quantify current trading exposures and compare them to established counterparty risk limits. VaR is now used regularly by non-financial corporations, pension plans and mutual funds, clearing organizations, brokers and futures commission merchants, and insurers.

"The world is an uncertain place and we can never know the maximum loss a firm might suffer. We all need to think carefully about those times when losses are more than the VaR.
This simple change in emphasis – talking about VaR "not as a 'worst case', but rather as a regularly occurring event with which we should be comfortable" (to use the words of Bob Litterman, formerly of Goldman Sachs) – would go far towards reminding us all that the proper role of VaR and quantitative risk tools is to inform and educate us about the uncertainty and randomness inherent in our world, not provide certainty that "the bank expects to lose no more than one amount". The future is random and contingent and we need to embrace this uncertainty rather than obscure it."

Thomas Coleman, Executive Director, Becker Friedman Institute for Research in Economics, University of Chicago[1]

As Choudry (2006) mentions, we have three basic approaches to calculate VaR:
The Variance-Covariance Approach (Correlation method) is the easiest way to produce a VaR distribution by calculating actual VaR statistics, by assuming that its distribution is normal with the mean and variance also characterizing a normal distribution.
The second approach is a historical simulation, which one of the popular ways of estimating VaR. It suggests using past data in a very direct way as a guide to what might happen in the future. Hull and White (1998) mention that this approach calculates potential losses based on actual

[1] http://www.ft.com/intl/cms/s/0/c85ff854-194c-11e2-af4e-00144feabdc0.html#axzz2ICUGSR5e

historical returns in the risk factors, so it captures the non-normal distribution of risk factor returns. Consequently, it takes into account changes that may occur over different periods of time. The three approaches mentioned in this paper all use historical data to estimate VaR, but this approach is completely based on historical price changes. The method is easy to calculate, but also has its disadvantages. Hull and White suggest updating the data, which shifts in volatility, so historical data should be adjusted in order to reflect these changes.

The third approach is the Monte Carlo simulation. The Monte Carlo simulation can be used when other simple approaches violation. This approach is especially useful with multidimensional problems (such as where outcomes will depend on more than one risk variable) and it will become even more attractive if the problem has more dimensionality. Choudry (2006) points out that this method is more flexible than the previous two methods, because it allows the risk manager to use actual historical distributions for risk factor returns rather than having to assume normal returns.

As we considered before, there are three main methods to calculate VaR. Financial institutions and companies can use the same method to calculate VaR, but there are still substantial differences in the application of VaR techniques. Different models can be used to measure the sensitivity of particular instruments to price movements; different methods can be used to aggregate exposures across instruments, and different techniques for estimating price volatility can be used.

2.2.1 Measures of VaR

To measure VaR, we must compute estimates for the first standard deviation and correlation. There are many studies on the prediction of volatility: stochastic volatility models (Taylor 1986) and realized volatility models (Anderson 2001). These models use historical stock price data to predict future volatilities. According to a paper we mainly focused on by Poon and Granger (2003), forecasts based on implied volatility are more accurate than forecasts based on historical returns. Also, research by Frijins, Tallau and Tourani-Rad (2009) shows that implied volatility is a good measure of volatility over the lifetime of an option. One important study which also used historically-based forecasts and option-implied forecasts to test the information content of ex-ante standard deviation and correlation estimates is James, Bodurtha and Qi (1999). In this paper, the new estimated parameters correlation gives relatively similar forecast information to that already created by implied volatility estimates. But if we consider much of the past literature, they provide widely varying conclusions about whether implied volatility gives significant results for the forecast of volatility. If we can find out which volatility input is best for financial crisis periods, risk managers and investment banks will have an opportunity to consider the best volatility covariance parameter estimates in order to provide more accurate VaR measurement.

2.3 Implied Volatility Index

Over the last 4 years, financial markets have been shocked by unexpected levels of volatility, with prices and market conditions changing very quickly both day-to-day and within a given day. This high level of volatility necessitates improvements in the accuracy of forecasting methods, the measurement of liquidity and reporting to key decision-makers, to enable organizations to make fact-based risk decisions in time, particularly with regard to market risk. One of the main inputs for VaR and other risk measurement methods is implied volatility. The Implied Volatility of an index is the volatility implied by an option price observed in the market. For a stock, we have many options with different strike prices and expiration dates, where each option can yield a different volatility implicit in the option's premium. Most of the time, even options with the same number of days remaining until expiration, but with different strike prices, will have different values of implied volatility. So, when using implied volatility in volatility analysis, it is necessary to calculate the representative implied volatility for a stock. We have many methods to calculate such a representative value. Christensen and Hansen (2002) said that the volatility implied in an option price helps forecast the future return volatility of an options market. If we have an effective market, we have the opportunity to get the best possible forecast features by using the information available to us.

2.4 Financial returns and Volatility inputs for VaR

Usually most stock prices are non-stationary, so as part of the measurement of market risk, the return series are chosen**.** Cambell, Lo and MacKinlay (1997) find two important advantages of using returns. The first case is that they are already a ready and completed summary, making them useful for the many investors who are interested in looking at the general brief conditions of many assets, as a return gives a scale-free summary of any investment opportunity. The other case is a return series comparison with price series, easy to use because of its good statistical